Outline of the Proposed Research Work Entitled

Development of Multimodal System using of Fusion Biometric traits: palm vein and face

Synopsis

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Abstract:

With the increasing demand for information security and security regulations all over the world, biometric recognition technology has been widely used in our everyday life. In this regard, multimodal biometrics technology has gained interest and became popular due to its ability to overcome a number of significant limitations of unimodal biometric systems. In my proposed research, a new multimodal biometric human identification system is proposed, which is based on a deep learning algorithm for recognizing humans using biometric modalities of face, and palm vein. , different fusion approaches will be employed to explore the influence of fusion approaches on recognition performance, therefore, feature and score level fusion approaches were applied.

Introduction:

The acceleration of the emergence of modern technological resources in recent years has given rise to a need for accurate user recognition systems in order to restrict access to the technologies. The biometric recognition systems are the most powerful option to date. Biometrics is the science of establishing the identity of a person through semi- or fully-automated techniques based on behavioral traits, such as voice or signature, and/or physical traits, such as the iris and the fingerprint [1]. The unique nature of biometrical data gives it many advantages over traditional recognition methods, such as passwords, as it cannot be lost, stolen, or replicated [2]. Biometric traits can be categorized into two groups: extrinsic biometric traits such as iris and fingerprint, and intrinsic biometric traits such as palm vein and finger vein. Extrinsic traits are visible and can be affected by external factors, while the intrinsic features cannot be affected by external factors [3]

In general, the biometric recognition system consists of four modules: sensor, feature extraction, matching, and decision-making modules [1]. There are two types of biometric recognition systems, unimodal and multimodal. The unimodal system uses a single biometric trait to recognize the user. While unimodal systems are trustworthy and have proven superior to previously used traditional methods, but they have limitations. These include problems with noise in the sensed data, non-universality problems,

and vulnerability to spoofing attacks, intra-class, and inter-class similarity [4].

Basically, multimodal biometric systems require more than one trait to recognize users [1]. They have been widely applied in real-world applications due to their ability to overcome the problems encountered by unimodal biometric systems [4]. In multimodal biometric systems, the different traits can be fused using the available information in one of the biometric system's modules. The four types of fusion include sensor-level fusion, feature-level fusion, score-level fusion, and decision-level fusion. The advantages of multimodal biometric systems over unimodal systems have made them a very attractive secure recognition method [1].

Several biometrics researchers have relied on machine learning algorithms for recognition purposes [5–9]. Machine learning algorithms require some extraction techniques to extract features from raw biometric data and transform the raw data into an appropriate format before classifying it. Moreover, machine learning algorithms require some preprocessing steps to be carried out prior to feature extraction. Furthermore, some extraction technologies do not always work successfully with different types of biometrics or different data sets of the same biometrics. Additionally, they cannot cope with biometric image transformations, for example, zooming and rotation [10]

Recently, deep learning has made a considerable impact and produced excellent results in biometrics systems [11–20]. The deep learning algorithms have overcome many of the limitations of other machine learning algorithms, particularly those associated with feature extraction techniques. Deep learning algorithms can cope with biometric image transformations and can extract features from raw data [21].

In view of the great performance of deep learning methods in various recognition tasks, this study aims to intensively investigate the use of the convolutional neural network (CNN) algorithm in recognizing a person from three biometric traits, which are face, iris, and finger vein. In my proposed research, an efficient multimodal biometric human identification system is proposed based on building a deep learning model for images of the face, and palm vein of a person. These traits have been chosen as the face is perhaps the most natural and, therefore, obvious individual

recognition trait, palm vein, has been added in regard to enhancing the accuracy of the identification result and improving the security and reliability of the proposed model. Palm vein is an intrinsic biometric trait, and unlike a fingerprint, finger vein cannot be affected by external factors and cannot be easily damaged, forged, or obscured. Moreover, the finger vein provides clear-cut dissimilarities between persons. At present, research on the fusion of these two types of biometrics is still very limited. To the best of our knowledge, no work has been carried out on a multimodal identification biometric system using three traits, one of which is finger vein. In addition, fusing the traits at two fusion levels: feature level fusion and score level fusion using two score methods, namely, the arithmetic mean rule and the product rule. SDUMLA-HMT, a publicly available real multimodal biometric dataset, is used for system evaluation. The proposed identification system relies on end-to-end CNNs models that extract features and then classify the person without deploying any image segmentation or detection techniques.

Literature Review

Several studies have proposed multimodal biometric systems that utilized a variety of recognition techniques. This section contains a review of recent studies that employed traditional machine learning and deep learning approaches in multimodal biometric systems

Discovering ways to combine different physical biometric traits has underpinned several recent biometric recognition studies. Bouzouina and Hamami [5] proposed a multimodal verification system that fused the face and iris traits at feature level fusion. The research employed various methods of feature extraction and applied support vector machines (SVM) algorithm for user verification and it produced an accuracy of 98.8%. Hezil and Boukrouche [6] proposed a biometric system that used the ear and palm print traits and fused them at the feature level. They developed texture descriptors and three classification methods. In another study, Veluchamy and Karlmarx [7] used unusual physical traits, finger vein, and knuckle traits to develop a multimodal biometric identification system. The system fused the traits at the feature level. The authors employed the K-SVM algorithm and their system achieved an accuracy of 96%.

Recently, Chanukya et al. [8] used the neural network to build a multimodal biometric verification system that recognized a human from their fingerprint and ear images. The system developed the modified region growing algorithm to extract shape features from the traits, and local Gabor Xor pattern to extract texture features from the traits. The proposed system achieved an accuracy of 97.33%. Furthermore, Ammour et al. [9] proposed a new feature extraction technique for a multimodal biometric system that relayed on face and iris traits. The iris feature extraction was carried out with a multi-resolution 2D Log-Gabor filter. While the facial features were extracted using singular spectrum analysis and normal inverse Gaussian. For the classification, fuzzy k-nearest neighbor (K-NN) was employed. The feature fusion was performed using score fusion and decision fusion.

On the other hand, some studies have focused on recognizing the users by behavioral biometric traits. In these systems, the feature recognition and extraction are difficult since behavioral traits do not offer reliably repeated patterns. Panasiuk et al. [11] tackled this problem by developing a system using K-NN classifier that recognized the user from a combination of mouse movement and keystroke dynamics. The proposed system reached an accuracy rate of 68.8%.

One of the studies that used deep learning algorithms for building a biometric system was conducted by Ding et al. [12]. In this study, a deep learning framework for face recognition was proposed. The framework used multiple face images and comprised eight CNNs for feature extraction and a three-layer stacked auto-encoder (SAE) for feature level fusion. Two different datasets were used to train the CNNs, namely CASIA-WebFace and LFW, which achieved accuracy rates of 99% and 76.53%, respectively. A study conducted by Al-Waisy et al. [13] proposed a multimodal biometric system for user identification, called IrisConvNet, which combined both the right and left irises using ranking-level fusion. The system firstly detected the iris region in the eye image, and then this detected region was entered into the CNN model. The system achieved a 100% recognition rate. In another study by the same authors, Al-Waisy et al. [14] developed a biometric identification system based on the face, and left and right irises. For face identification, a face detection region method was used, and then a deep belief network (DBN) was applied. For iris identification, IrisConvNet [13] was used. Various matching score fusion

methods were employed and the accuracy of the proposed system was 100%.

Soleymani et al. [15] proposed a multimodal CNN where the iris, face, and fingerprint features were fused at different levels of CNN. The authors used two fusion methods, which were multi-abstract fusion and weighted feature fusion algorithms. The evaluation results showed that using the three types of biometrics gave the best result. In further research [16], the authors proposed a compact bilinear feature fusion algorithm to fuse the features at the fully connected layer. The proposed algorithm was evaluated using different biometric traits (irises, faces, fingerprints) from different datasets. In another study, Gunasekaran et al. [17] proposed a deep contourlet derivative weighted rank (DCDWR) framework. DCDWR used iris, face, and fingerprint traits to recognize a person. Contourlet Transform was applied in the framework for performing preprocessing on input images.

A local derivative ternary algorithm was developed for extracting multimodal features. The acquired features from local derivative ternary were fused by using weighted rank level fusion and stored in a database for matching. Finally, a deep learning template matching algorithm was developed to verify the user identity

Some deep learning research has intended to use finger vein for user recognition. For example, Kim et al. [18] built a multimodal biometric recognition system based on CNN by fusing finger vein and finger shape. A ResNet pretrained model was used, and the two traits fused at the score level using several fusion methods, which were weighted sum, weighted product, Bayesian rule, and perceptron rule. Moreover, Liu et al. [19] used the CNN algorithm to build a recognition system that received multiple finger vein images. They developed the CNN model based on the AlexNet pertained model. The model was trained using the SDUMLA dataset, and it obtained an accuracy rate of 99.53%. Recently, Boucherit et al. [20] used finger vein traits to build an identification model, developing a merge CNN model that used several identical CNNs with different input image qualities. The authors conducted different experiments using different network parameters and layers. The most optimal model took a combination of original images and images enhanced with the contrast limited adaptive histogram (CLAH) method. The model was trained using

the FV-USM, SDUMLA-HMT, and THU-FVFDT2 datasets, and it achieved a recognition rate of 96.75%, 99.48%, and 99.56%, respectively.

In general, deep learning models are not trained from scratch; as deep learning demands a large dataset. Training from scratch with deep learning is a lengthy process that involves complex experimentations with different parameter values, for example, weights, number of filters and layers, amongst others. This is the reason why most researchers use pre-trained models, for example, Inception, VGGNet, AlexNet, DenseNet [22]. A previous study by Nguyen et al. [23] proved the success of using five different CNN pre-trained models for iris recognition. The five pre-trained models are VGGNet, Inception, AlexNet, ResNet, and DenseNet. DenseNet achieved the highest accuracy, followed by ResNet, Inception, VGGNet, and AlexNet.

From the previous work in literature, it can be noticed that the most used machine learning algorithm in recent research is SVM [5–7]. Moreover, when using machine learning approach to recognize biometrics, the biometrics images require specialized feature extraction algorithms depending on the biometric type. Sometimes the images need several pre-processing stages [5–7]. While in deep learning approach, the deep learning network itself extracts the features from the images automatically. The performance of deep learning approaches is generally better than the performance of the machine learning approaches. However, these deep learning-based approaches, while effective, are very computationally expensive and time consuming [11–20]. In addition, studies deploying deep learning algorithms in multimodal biometric systems [13–20] begin the experimentation process by applying region detection methods prior to entering data into deep learning model. The use of region detection methods requires first selecting a suitable technique for a particular trait, also, the process can be time-consuming [1]. It is also noticed that the physical biometric traits deliver better performance than behavioral biometric traits [11]. Moreover, the iris trait has a tendency to increase the accuracy rate [13,14]. The last important note is that few studies have used finger vein trait in biometric multimodal systems with deep learning models.

Based on what has been observed in previous studies, this work develops an identification multimodal biometric system that combines

face, iris, and finger vein images using the CNN model. Feature level fusion and score level fusion, with different score methods, were applied in order to find out the most effective approach. An end-to-end CNN algorithm will be used to extract features and recognize images.

Objectives of the study:

The objective of this study can be listed below:

- To provide an overview of the most efficient techniques for the fusion of multimodal biometric traits.
- To develop and implement a method for fusion of a minimum of two biometric traits based on deep learning
- To evaluate and analyze the performance of the developed method in order to clarify their efficiency and effectiveness by comparing them to some previous methods of a multimodal biometric system.
- To give recommendations and conclusions for future enhancement.

Methodology:

- Analyzing and evaluating the different existing multimodal biometric system (face and palm vein) using Deep learning techniques
- Develop new method deep learning-based for fusion of multimodal biometric system with desirable efficient.
- Implement the proposed method on any Deep learning framework such as TensorFlow, Keras, PyTorch.
- Using any analyzing tools for testing and validating the proposed work.

Significance of study:

A multimodal biometric model is proposed to be developed for user identification. The proposed system employed deep learning techniques. Feature level fusion to identify the user from their face, and palm vein traits. To my knowledge, there are few like this study to investigate the use of deep learning algorithms for a multimodal biometric model with multi traits. It is good to use multi three biometric traits in identification systems can obtain better results than using one biometric trait. The previous research's results also revealed that incorporating multi-trait into a

multimodal biometric model could lead to a better identification accuracy when compared with fingerprint trait.

Schedule.

Year 1:

- Literature Survey.

Year 2:

- Theoretical analysis of the existing Deep learning Techniques for the fusion of multimodal biometric traits

Year 3:

- Develop a new deep learning-based model for achieving high efficient methods for the fusion of multimodal biometric traits.
- Assessment of experimental results in terms of comparison.

Year 4:

- Interpretation of the experimental results.
- Preparation of final synopsis and thesis.
- Submission of synopsis and thesis.

References

1. Jain, A.K.; Ross, A.A.; Nandakumar, K. *Introduction to Biometrics*; Springer Science & Business Media: Berlin, Germany, 2011; ISBN 9780387773254.
2. Lumini, A.; Nanni, L. Overview of the combination of biometric matchers. *Inf. Fusion* **2017**, *33*, 71–85.
3. Shaheed, K.; Liu, H.; Yang, G.; Qureshi, I.; Gou, J.; Yin, Y. A systematic review of finger vein recognition techniques. *Informatics* **2018**, *9*, 213.
4. Oloyede, M.; Hancke, G. Unimodal and Multimodal Biometric Sensing Systems: A Review. *IEEE Access* **2016**, *4*, 7532–7555. *Sensors* **2020**, *20*, 5523
5. Bouzouina, Y.; Hamami, L. Multimodal biometric: Iris and face recognition based on feature selection of iris with GA and scores level fusion with SVM. In Proceedings of the 2017 2nd International Conference on Bio-Engineering for Smart Technologies, Paris, France, 30 August–1 September 2017; pp. 1–7.
6. Hezil, N.; Boukrouche, A. Multimodal biometric recognition using human ear and palmprint. *IET Biom.* **2017**, *6*, 351–359.
7. Veluchamy, S.; Karlmarx, L.R. System for multimodal biometric recognition based on finger knuckle and finger vein using feature-level fusion and k-support vector machine classifier. *IET Biom.* **2017**, *6*, 232–242.
8. Chanukya, P.S.V.V.N.; Thivakaran, T.K. Multimodal biometric cryptosystem for human authentication using fingerprint and ear. *Multimed. Tools Appl.* **2020**, *79*, 659–673.
9. Ammour, B.; Boubchir, L.; Bouden, T.; Ramdani, M. Face–iris multimodal biometric identification system. *Electronics* **2020**, *9*, 85.
10. Zhang, Q.; Yang, L.T.; Chen, Z.; Li, P. A survey on deep learning for big data. *Inf. Fusion* **2018**, *42*, 146–157.
11. Panasiuk, P.; Szymkowski, M.; Marcin, D. A Multimodal Biometric User Identification System Based on Keystroke Dynamics and Mouse Movements. In Proceedings of the 15th IFIP TC 8 International Conference on Computer Information Systems and Industrial Management, Vilnius, Lithuania, 14–16 September 2016; pp. 672–681.
12. Ding, C.; Member, S.; Tao, D. Robust Face Recognition via Multimodal Deep Face Representation. *IEEE Trans. Multimed.* **2015**, *17*, 2049–2058
13. Al-Waisy, A.S.; Qahwaji, R.; Ipson, S.; Al-Fahdawi, S.; Nagem, T.A.M. A multi-biometric iris recognition system based on a deep learning approach. *Pattern Anal. Appl.* **2018**, *21*, 783–802
14. Al-Waisy, A.S.; Qahwaji, R.; Ipson, S.; Al-Fahdawi, S. A multimodal biometrie system for personal identification based on deep learning approaches. In Proceedings of the 2017 Seventh International Conference on Emerging Security Technologies, Canterbury, UK, 6–8 September 2017; pp. 163–168.
15. Soleymani, S.; Dabouei, A.; Kazemi, H.; Dawson, J.; Nasrabadi, N.M. Multi-Level Feature Abstraction from Convolutional Neural Networks for Multimodal Biometric Identification. In Proceedings of the 2018 24th International

Conference on Pattern Recognition, Beijing, China, 20–24 August 2018; pp. 3469–3476.
16. Soleymani, S.; Torfi, A.; Dawson, J.; Nasrabadi, N.M. Generalized Bilinear Deep Convolutional Neural Networks for Multimodal Biometric Identification. In Proceedings of the 2018 25th IEEE International Conference on Image Processing, Athens, Greece, 7–10 October 2018; pp. 763–767.
17. Gunasekaran, K.; Raja, J.; Pitchai, R. Deep multimodal biometric recognition using contourlet derivative weighted rank fusion with human face, fingerprint and iris images. *Automatika* **2019**, *60*, 253–265
18. Kim, W.; Song, J.M.; Park, K.R. Multimodal biometric recognition based on convolutional neural network by the fusion of finger-vein and finger shape using near-infrared (NIR) camera sensor. *Sensors* **2018**, *18*, 2296.
19. Liu, W.; Li, W.; Sun, L.; Zhang, L.; Chen, P. Finger vein recognition based on deep learning. In Proceedings of the 2017 12th IEEE Conference on Industrial Electronics and Applications, Siem Reap, Cambodia, 18–20 June 2017; pp. 205–210.
20. Boucherit, I.; Zmirli, M.O.; Hentabli, H.; Rosdi, B.A. Finger vein identification using deeply-fused Convolutional Neural Network. *J. King Saud Univ. Comput. Inf. Sci.* **2020**.
21. Jürgen Schmidhuber Deep learning in neural networks: An overview. *Neural Networks* **2015**, *61*, 85–117.
22. Chollet, F. *Deep Learning with Python*; Manning Publications: New York, NY, USA, 2018; ISBN 9781937785536
23. Nguyen, K.; Fookes, C.; Ross, A.; Sridharan, S. Iris Recognition with Off-the-Shelf CNN Features: A Deep Learning Perspective. *IEEE Access* **2017**, *6*, 18848–18855.

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